Lawrence Berkeley National Laboratory

Linking measurements and models in commercial buildings: A case study for model calibration and demand response strategy evaluation

By: Rongxin Yin, Sila Kiliccote, Mary Ann Piette

Lawrence Berkeley National Laboratory

December 2014

This work described in this paper was coordinated by the University of California at Berkeley, Siemens Corporation Research, and the Lawrence Berkeley National Laboratory (LBNL) Demand Response Research Center and was funded by the U.S. Department of Energy, under DOE contract DE-AC02-05CH11231, Award Number DE-EE0003847. The authors are grateful for the extensive support from the Auto-DR program managed by the Demand Response Research Center at LBNL. Special thanks to Prof. David Culler, Prof. David Auslander, and Therese Peffer for providing their insight and support, and to Jianmin Zhu from Siemens Corporate Research. Thanks also to University of California building manager Domenico Caramagno for providing technical support..

Linking measurements and models in commercial buildings: A case study for model calibration and demand response strategy evaluation

Prepared by

LAWRENCE BERKELEY NATIONAL LABORATORY
Berkeley, CA

Rongxin Yin
Sila Kiliccote
Mary Ann Piette

Dec 2014

Abstract

The use of simulation to evaluate energy-efficient operations, commissioning problems, and demand-response (DR) strategies offers important insights into building operations. This paper describes a step-by-step procedure for using measured end-use energy data from a campus building to calibrate a simulation model developed in EnergyPlus. This process included identification of key input parameters for reducing uncertainties in the model. The building geometry and internal thermal zones were modeled to match the actual heating ventilation and air conditioning (HVAC) zoning for each individual variable air-volume (VAV) zone. We evaluated most key building and HVAC system components, including space loads (actual occupancy number, lighting and plug loads), HVAC air-side components (VAV terminals, supply and return fans) and water-side components (chillers, pumps, and cooling towers). Comparison of the pre- and post-calibration model shows that the calibration process greatly improves the model's accuracy for each end use. We propose an automated model calibration procedure that links the model to a real-time data monitoring system, allowing the model to be updated any time. The approach enables the automated data feed from sMAP into the EnergyPlus model to create realistic schedules of space loads (occupancy, lighting and plug), performance curves of fans, chillers and cooling towers. We also field-tested DR control strategies to evaluate the model's performance in predicting dynamic response effects. Finally, this paper describes application of the calibrated model to analyze control systems and DR strategies with the goal of reducing peak demand. We compare end-use data from modeled and actual DR events.

Keywords: Model calibration; Automated model calibration; Demand response; DR strategies; Demand reduction; CO_2 concentrations

Table of Contents

1 Introduction 6
2 Model development 8
 2.1 Building description 8
 2.2 Model development 9
  2.2.1 Weather data 9
  2.2.2 Zoning 10
  2.2.3 Internal loads 10
  2.2.4 Building system loads 11
3 Model calibration 11
 3.1 Space loads 13
  3.1.1 Occupants 13
  3.1.2 Lighting and plug loads 15
 3.2 Air-side components 17
  3.2.1 Variable air volume 17
  3.2.2 Air-handling units 18
 3.3 Water-side components 19
4 Results 21
 4.1 Lighting, plug, air-handling unit, and cooling plant power usage 21
 4.2 The Model's Prediction of Dynamic Response 23
5 Application of the calibrated model to demand response 25
6 Discussion 26
7 Summary and Conclusions 27
8 Acknowledgments 28
9 References 28

List of Figures

Figure 1: 3D Image of the EnergyPlus simulation model of the case-study building 9
Figure 2: Thermal zoning of the case-study building model's 4th floor 10
Figure 3: Schematic of Automated EnergyPlus Model Calibration.. 13
Figure 4: Estimated occupancy profile in an open office area on a test day 14
Figure 5: Estimated occupancy profile in an open office area over two weeks 15
Figure 6: Calibrated 4th-floor lighting power schedules on weekdays and weekends 16
Figure 7: Calibrated 4th-floor plug power schedules on weekdays and weekends..................................... 16
Figure 8: Comparisons of design, Title 24-2008, and ASHRAE 62.1-2007 minimum ventilation rates ... 18
Figure 9: Comparison between reference and actual operational fan part-load curves 19
Figure 10: Validation of the new supply fan operational curve 19
Figure 11: Electrical input to cooling output ratio function of part-load ratio curve................................. 19
Figure 12: Validation of calibrated chiller model curve – Electric input to cooling output ratio 20
Figure 13: Cooling tower fan power ratio as function of airflow ratio 20
Figure 14: Comparison of measured and simulated lighting and plug load power usage during a week in summer 2011 21
Figure 15: Comparison of sub-metered power usage of supply fans, return fans, and two exhaust fans ... 22
Figure 18: Comparison of cooling tower measured and simulated power usage during a test week 23
Figure 17: Comparison of measured and simulated supply and return fan power during a DR test event. 24
Figure 18: Comparison of peak demand reduction from HVAC system for all control scenarios 25
Figure 19: Comparison of peak demand reduction from AHUs for all control scenarios 26

List of Tables

Table 1: Comparison of different model calibration methods 7
Table 2: Key parameters of building HVAC system components 11
Table 3: Acceptable calibration tolerances 12
Table 4: Comparisons of initial estimated and calibrated plug load on each floor 17
Table 5: Results of model calibration based on monitoring data 23
Table 6: Comparison between measured and simulated AHU performance during a DR test event (Peak outside air temperature: 70°F) 24

1 Introduction

The engineering, controls, and buildings energy research community is developing a number of building energy optimization and advanced control concepts to reduce energy use and enable demand-response (DR) capabilities in buildings. To accurately model the effect of optimal control strategies, a detailed simulation model is needed that produces highly accurate results for each of the building's mechanical system components. The objective of this study is to demonstrate a new approach to develop and automating calibration of a model that can be used to evaluate the effect of various DR control strategies on peak demand reduction. The calibrated simulation model can be implemented in building energy management systems (BEMs) to assist building operators in predicting the effects of various control strategies.

For modelers, an advantage of a building simulation physical model is that it enables them to evaluate various design strategies, energy conversation measures (ECMs), and building system operational modes and to choose an optimal operational scheme for achieving a given target, such as reducing demand or maximizing energy efficiency. Calibration of such a model is critical; the model must closely approximate the actual building being studied to ensure that costly mistakes are avoided. A number of studies demonstrate that simulation models provide valuable support for conceptual and integrated system design, enabling designers to evaluate new architectural concepts and the impacts of different types of building façades; daylighting, solar shading, passive cooling, and integrated control strategies; and other design elements. However, when building energy simulation moves from the design phase to the operational phase, there are many uncertainties in models' ability to accurately reflect actual building performance, especially on a large scale. As reported in a study of Energy Performance of Leadership in Energy Efficiency and Design (LEED) for New Construction Buildings (Turner and Frankel, 2008), discrepancies between simulated and measured energy use intensity show an acceptably close match between simulated and measured values for only a small number of buildings.

Empirical validation methods have traditionally been used to evaluate the accuracy of models for simulating the energy intensity of existing buildings, to identify model uncertainties, and to calibrate input variables by comparing them to measured values. Empirical validation has been demonstrated in many field studies (Pan et al., 2008; Yin et al., 2010; Raftery et.al, 2011; Yin et al., 2012; Wang et.al, 2013; O'Neill et.al, 2013). Among the milestones in model calibration was the development of a systematic method using a "base load analysis approach" (Yoon et al., 2003), which uses a combination of monthly utility billing data and sub-metered data to calibrate a building energy performance model. A case study of this approach showed that it reliably and accurately simulated monthly and annual building energy requirements. Another key study by Reddy et al. (2007) proposed a general methodology for calibrating detailed building energy simulation programs based on performance data and applied this methodology to three case-study office buildings. In that study, building system loads were characterized as "weather dependent" (HVAC system loads) and "weather independent" (e.g., lighting and plug loads). Pan et al. (2008) calibrated a simulation model in a high-rise commercial building using a step-by-step method based on the approach proposed in American Society of Heating, Refrigerating, and Air Conditioning Engineers (ASHRAE) Guideline 14-2002. In 1994, Norford et al. presented a common-sense procedure for calibrating a DOE-2 computer model of a commercial building, identifying the major building loads, including lighting and equipment. New eta al. (2012) introduced an "Autotune" methodology for calibrating building energy models by using a suite of machine-learning algorithms, parameter sensitivity analysis and sensor data. Finally, O'Neill and Eisenhower (2013) proposed a systematic, automated way to calibrate a building energy model. Their optimization-based approach leveraged the analysis of parametric uncertainty with parametric simulations minimizing the error between the simulated and measured data.

Table 1 compares different types of model calibration methods in terms of their applications, advantages, and disadvantages.

Table 1: Comparison of different model calibration methods

Model calibration method	Application	Advantages	Disadvantages
Monitoring-based	Forward model; data-driven model	• Detailed physical parameters for each component • Valid and credible • Large-scale model with calibration possible for sub-level system or component • Accurate	• Expensive and time consuming • Lack of monitoring data • Large number of parameters for each component
Optimization-based	Forward model; data-driven model	• Inexpensive • Automatic calibration process possible • Many or few input parameters • Very accurate	• A lot of computing time possibly required to minimize error • Not necessarily realistic
Regression model-based (ASHRAE Inverse Modeling Toolkit)	Data-driven model	• Fast and inexpensive • Few input parameters • Very accurate	• Lack of flexibility • Mostly used for baseline model development

A key question is whether large-scale simulations have low predictive value in existing buildings. The answer is no, but intense calibration is needed to sufficiently reduce model uncertainties in order to achieve high predictive value in large-scale, highly complex simulations. For simulating building energy in these situations, a good solution is to break the model calibration problem down into smaller, sub-level systems and manageable segments. Calibrating each smaller segment of the building improves the model's overall predictive value. Typically, a building's energy usage is composed of lighting, plug, and HVAC system loads. Lighting and plug loads are assumed to be weather-independent variables even though lighting power consumption is influenced by daylighting. This portion of load can be measured by sub-metering on each floor of a building. HVAC power usage is driven by a number of factors, including weather, internal loads (occupant, light, and plug), HVAC equipment specifications, and system configurations and control schemes. As more and more building information becomes available, a critical problem is enabling the simple and efficient transmission of building energy data to the simulation model.

Another challenge for building simulation models is to predict buildings' behavior under dynamic conditions such as DR events or to evaluate the effects of energy-saving strategies such as peak-demand reduction. Several past studies have looked at modeling these types of dynamic control strategies. Rabl et al. (1991) studied the application of DR simulation models in commercial buildings, developing a data-driven based dynamic model to simulate the effect of different thermostat control strategies for reducing peak demand. Morris et al. (1994) investigated two optimal dynamic building control strategies in a representative room in a large office building; experiments showed as much as 40% reduction in peak cooling load from this approach.

Several studies have demonstrated building control strategies for reducing peak load that are applicable to our objective of using the calibrated simulation model to model peak-load reduction approaches. Keeney et al. (1997) developed a building control strategy and tested it in a large office building, finding that pre-cooling could limit peak cooling loads to 75% of cooling capacity. Xu et al. (2004) demonstrated the potential for reducing peak electrical demand in moderate-size commercial buildings by modifying HVAC system control. Field tests of this approach showed that chiller power was reduced by 80-100% (1 - 2.3 watts per square foot [W/ft^2]) during the peak period without thermal comfort complaints from occupants. Xu et al. (2005) conducted a series of field tests in two commercial buildings in Northern California to investigate the effects of various pre-cooling and demand-shed strategies. These tests showed the potential to reduce cooling load 25-50% during peak hours and demonstrated the importance of discharge strategies to avoid rebounds. Braun (2003) presented an overview of research related to the use of building thermal mass for shifting and reducing peak cooling loads in commercial buildings and provided specific results obtained through simulations, laboratory tests, and field studies.

Peak-load reduction strategy modeling studies include Yin et al. (2010); this study developed and calibrated simulation models of 11 commercial buildings for evaluating the effect of different thermostat control strategies. There have been a number of other simulations, laboratory and field tests, and pilot studies on DR in buildings (Motegi, 2007; Piette et al., 2007).

This paper adds to the body of research on model calibration and application to dynamic building scenarios such as DR events by developing an EnergyPlus model for a campus office building and calibrating it with actual measured data from the building's energy management system. To calibrate the model's foundation, we modeled the building geometry and internal thermal zones to match the actual HVAC zoning for each individual variable air-volume (VAV) zone. Following an evidence-based methodology, the model was developed from (1) as-built architectural, mechanical design, and control drawings; (2) actual building operation and behavior (occupancy, lighting and plug loads, HVAC system operations); and (3) detailed mechanical equipment specifications and actual operational performance (part-load operational curves of chiller, pump and fan, etc.). We propose an automated calibration procedure that links the model to the building's real-time data monitoring system so that the model can be updated with measured data at any time, especially when there is any change in building system operations or when energy-efficiency measures are implemented. We used the calibrated model to evaluate the effect of different DR control strategies for peak-load reduction.

2 Model development

Building simulations often start with building load calculations using outdoor weather conditions and the building's physical description. The building heating/cooling load is then transferred within the model to the system load to calculate the performance of air-side system components (e.g., supply and return fans, VAV terminals). Finally, the system load is used to calculate the plant load (e.g., chillers, cooling towers, pumps and auxiliary equipment). Generally, the goal of model calibration is to eliminate uncertainties in model inputs. There are limited assumptions and uncertainties in model of the physical building, including building geometry and envelope, but there are many uncertainties in model inputs for other components, such as weather data, space loads, HVAC system component actual performance, and building operational schedules. Overall, the model's accuracy depends on how much detailed information is available from the building. The first step in developing a model includes the collection of model input data – weather, building physical details, space loads (occupant, lighting and plug loads), mechanical systems (equipment specifications and relevant control sequences), energy usage, and utility bills. Yin et.al (2010) describe a general procedure for model development and calibration.

2.1 Building description

We performed a case study of an existing office building on campus that was built in 2008. The building is 141,000 square feet, with classrooms, offices, laboratories and a 149-seat auditorium. It houses offices and a nano-fabrication lab. Several issues require special attention in this facility. First, the silicon-wafer fabrication laboratory with a large clean room occupies several floors of the building. The chilled water loop of the building is shared with this laboratory. The building operator requested that no services be changed in the laboratory part of the building under any circumstances. In addition, the building has two 600-ton chillers: a steam-powered absorption chiller and an electric centrifugal chiller. The centrifugal chiller operates during the winter for higher plant efficiency, and the absorption chiller is used during the summer to take advantage of redundant steam on campus. Thus, at any given time, only one of the chillers is operating; even so, each chiller is grossly over-sized for the building loads, so it short-cycles excessively.

The building monitoring system has two main substations, a dozen sub-meters, and thousands of sensors. A comprehensive whole-building sub-metering system was installed to monitor power usage of process equipment, lighting and plugs on each floor, air-handling units (AHUs), the electrical chiller, and all other equipment components.

2.2 Model development

The initial EnergyPlus model created for the case study building followed the standard practices for creating advanced energy models; the physical structure was modeled, including appropriate mechanical system modules and standard ASHRAE assumptions for weather, ventilation, lighting, plug loads, and other attributes. Detailed modules that correspond to the actual VAV zones were also modeled. Yet, even with this substantial effort, energy usage results generated by the model differed significantly from actual building performance. Figure 1 shows the three-dimensional model of the case-study building.

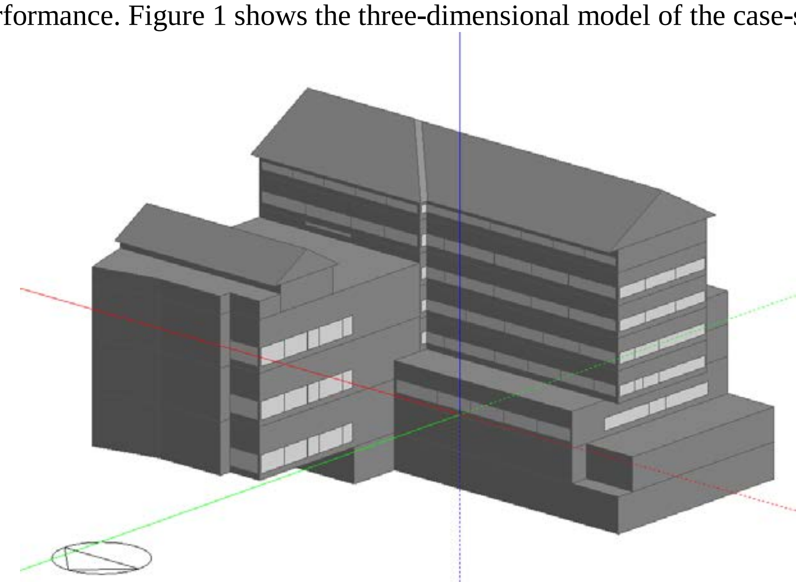

Figure 1: 3D Image of the EnergyPlus simulation model of the case-study building

2.2.1 Weather data

Weather is one of the most important factors in predicting a building's energy performance. Actual weather data are necessary for calibrating a simulation model with measured data from buildings. Traditionally, energy model practitioners use weather data from the National Weather Station nearest the building site. In this study, an on-site weather station was used to capture the micro-climate variation in the area where the building is located. A full set of weather data points was collected from the local on-site station, including the dry-bulb temperature, dew point temperature, relative humidity, solar radiation, wind speed/direction, and precipitation. Those weather data points were customized into the EnergyPlus weather file to be used in the simulations.

2.2.2 Zoning

Zoning is a method of simplifying an energy model while maintaining a reasonable level of accuracy. The degree of simplification entailed in zoning depends on the intended use of the model, e.g., for architectural design, code compliance, green building rating, evaluating ECMs, or other types of analysis. For typical model usage, the general criteria for thermal zoning include taking into account zone functionality, orientation, thermostat control, and whether a zone is perimeter or interior.

For modeling of existing buildings, utilizing all available information is essential. In this study, a BMS provides the characteristics of each building system component. For example, for a VAV box, we can derive a full set of parameters from the BMS, including minimum/maximum airflow rates in cooling/heating mode, damper position, and the reheat coil valve position. In order to avoid a mismatch between thermal zone and VAV box in EnergyPlus, we used the area served by each VAV terminal as the basis for determining the zones in the model as shown in Figure 2. The advantage of this approach is that it captures the actual performance of VAV terminals and makes calibration easier.

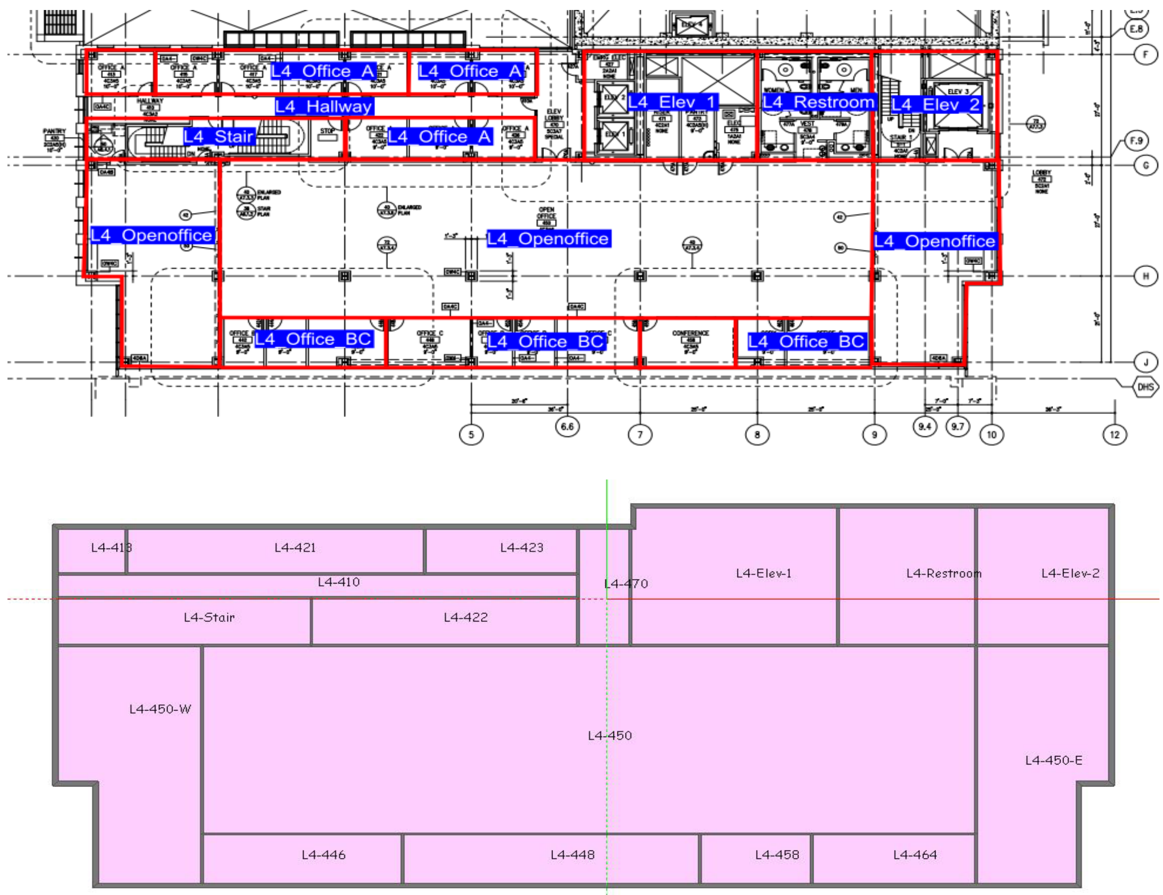

Figure 2: Thermal zoning of the case-study building model's 4th floor

2.2.3 Internal loads

Most buildings don't have a sub-metering system for monitoring energy usage of each building system component. And in many buildings, the actual performance of the space load can differ significantly from the designed operation. During initial model development, the best way to simulate space load is following the relevant code or standard. ASHRAE standards 62.1, 90.1 and Title 24 standard are used to determine occupant density and the lighting and plug load densities, respectively, in each type of zone. Inputs from the standards would be used if no sub-metered data from the building were available.

2.2.4 Building system loads

Equipment specifications and building HVAC schedules provide all important characteristics for each system component, including air-side components (VAVs, AHUs, return and exhaust fans, etc.) and water-side components (chillers, cooling towers, chilled/condenser water pumps, rooftop air-conditioning units, etc.). For each component, all key parameters are identified as shown in Table 2.

Table 2: Key parameters of building HVAC system components

Air-side components	Parameters	Water-side components	Parameters
Thermostat setpoints	Each system control zone's thermostat temperature set point	Steam absorption chiller	Nominal capacity, entering/leaving water temperature and flow rate at evaporator and condenser, steam load at generator, associated pump power, operating temperature setpoints
VAV terminals	Minimum/maximum airflow rates under cooling/heating mode	Electric centrifugal chiller	Nominal capacity, coefficient of performance, entering/leaving water temperature and flow rate at evaporator and condenser, operating temperature set points, operating curves
Supply/return fans in AHUs	Supply airflow rate, supply fan power, pressure, part-load curve	Pumps	Type, water flow rate, nominal power
Exhaust fans	Fan power, airflow rate, operating efficiency	Cooling towers	Nominal capacity, entering/leaving water temperature and flow rate under design conditions, tower fan power, part-load curve, operating temperature set points
Coils in AHUs	Cooling capacity, entering/leaving chilled water temperature, water flow rate	Rooftop units	Nominal capacity, characteristics of supply fan and cooling coil

3 Model calibration

The purpose of calibrating a model is to obtain accurate and high-quality simulation results that show good agreement with measured data (Pan et al., 2008; Yin et al., 2010). Several standards and guidelines provide the acceptable calibration tolerance of the cumulative variation of root mean squared error

(CVRMSE) and the mean bias error (MBE) for annual, monthly, and hourly data calibration. A simulation model can thus be calibrated until it satisfies all of these criteria. Here are definitions of each metric used in the following equation: M (Measured), S (Simulated), and N (Number of month).

$$MBE_{month}(\%) = \left[\frac{(M - S)_{month}}{M_{month}} \right] \times 100\%$$

$$CV(RMSE_{month})(\%) = \left[\frac{RMSE_{month}}{\overline{M}_{month}} \right] \times 100\%$$

$$RMSE_{month} = \left\{ \frac{\left[\sum_{month} (M - S)^2_{month} \right]}{N_{month}} \right\}^{1/2}$$

$$\overline{M}_{month} = \frac{\sum (M_{month})}{N_{month}}$$

Table 3 presents the acceptable tolerances for monthly and hourly data calibration according to ASHRAE Guideline 14. Our initial models were calibrated to achieve the acceptable monthly tolerances based on the required MBE and CV(RSME) then again calibrated based on hourly data to increase accuracy.

Table 3: Acceptable calibration tolerances

Calibration Type	Index	Acceptable Value
Monthly	MBE_{month}	±5%
	$CV(RMSE_{month})$	15%
Hourly	MBE_{hour}	±10%
	$CV(RMSE_{hour})$	30%

In this study, the purpose of calibrating the model was not only to evaluate the whole-building energy performance, but also to provide accurate simulation results for major building system components to accurately capture the effect of various DR strategies. Generally, models will be calibrated to the level of whole-building utility measurements. However, in some cases, a model with good calibration of the whole-building energy usage does not produce accurate results for each end use. Therefore, we began by calibrating the model at the level of each component end use, e.g., lighting, plugs, supply fans, chillers, and other sub-metering end uses. Whole-building energy usage can be easily calibrated once the components have been calibrated.

The simple measuring and actuation profile (sMAP) allows instruments and other producers of physical information to directly publish their data, which is a great tool for studying buildings, allowing organization and querying of large repositories of physical data from BMSs. In this study, sMAP was used to collect and retrieve the data. There sMAP and the EnergyPlus simulation models can be bridged by exchanging monitoring data points and model data inputs. This data exchange speeds up the process of model calibration because model data inputs do not have to be manually validated. In addition, the process of model calibration can take place off line or in real time on line. Figure 3 presents a schematic of automated EnergyPlus model calibration based on linking the sMAP and the model.

Most previous research work in the field of model development and calibration focuses on the whole-building level to evaluate the effects of ECMs, building HVAC system control strategies, and so on. For a commercial building, whole-building energy usage is composed of the HVAC system, lighting and plug, and miscellaneous loads. A model that is well calibrated at the whole-building level might give an unreasonable breakdown at the sub-utility level. For DR studies, demand savings come from each load category: fan, chiller, pump, cooling tower, and lighting and plug loads. Therefore, it is essential to validate all relevant system components' performance to ensure a high level of model accuracy. Generally, the building geometry and envelope are modeled as they are, and there is limited potential for model calibration for these components once they are verified by a field survey. As mentioned above, a key activity during this portion of the process is to define the internal thermal zones within the building. There is a commonly known trade-off among simplification (zoning), simulation speed, and model accuracy. After the model is developed, component-based calibration can be used to verify space loads and HVAC system and plant loads, step by step. Raftery et.al (2011) describe such an evidence-based model calibration methodology, and Wang et al. (2013) describe a comparable monitoring-based HVAC commissioning method.

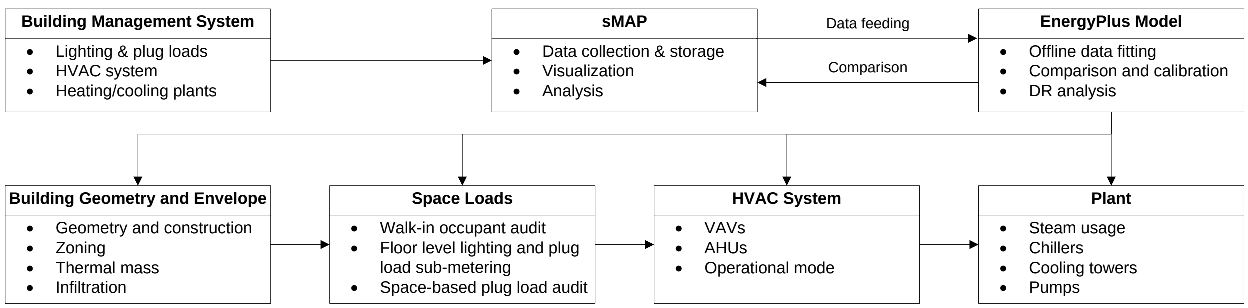

Figure 3: Schematic of Automated EnergyPlus Model Calibration

3.1 Space loads

Space loads usually account for nearly one-third of whole-building power usage in commercial office buildings (CBECS, 2012). During field surveys, it is easy to estimate the number of people and behavior in a building. However, as noted above, most buildings don't have sub-metering systems to measure actual lighting and plug load power consumption. The result is over- or under-estimation of lighting and plug loads, which affects subsequent simulations of the HVAC system and plant loads.

3.1.1 Occupants

To enable estimation of the number of building occupants and the carbon dioxide (CO_2) concentrations of outdoor fresh air and indoor air for the study building, the BMS and sensors monitored the outdoor air damper position and the supply airflow rate. CO_2 measurement sensors were calibrated to be less than 75 ppm – the accuracy specification in California's Title 24 standard. On a test day, actual hourly occupancy profiles were recorded by counting the number of occupants in the open-plan office area on the study building's fourth floor, as shown in Figure 4. Two algorithms for estimating the number of occupants are: steady-state (ASHRAE standard 62-1989R) and dynamic detection (S. Wang et al., 1999).

$$P \cdot S + E_{ac} m_{OA}(C_{OA} - C_R) = V \frac{dC_R}{d_t}$$

Steady-state detection algorithm:

$$P = \frac{E_{ac} m_{OA}(C_R - C_{OA})}{S}$$

Dynamic detection algorithm:

$$P = \frac{E_{ac}(m_{OA}^i + m_{OA}^{i-1})(C_R^i - C_{OA}^i)}{2S} + V \frac{C_R^i - C_R^{i-1}}{S\Delta t}$$

Where,

P: Number of occupancy in the space

S: Average CO_2 generation rate of an occupant, m^3/h
E_{ac}: Air change effectiveness
m_{OA}: Outside air volume flow rate, m^3/h
C_{OA}: CO_2 concentration of the supply air, ppm
C_R: CO_2 concentration of the return air, ppm
V: Air volume of the space, m^3/h

Figure 4 compares estimated and recorded occupant profiles on a workday. The estimated occupancy profile is calculated at 15-minute intervals based on the dynamic detection algorithm of the outdoor airflow rate and indoor and outdoor CO_2 concentrations. We can see that, during the typical lunch-hour period of 12pm to 2pm, most occupants left the building. At the same time, frequent opening of office doors pushed more fresh air into the office space, which was not captured in the monitoring system, and the estimated number of occupants was lower than recorded. However, overall, the estimated occupancy profile tracks true occupancy patterns on this test day well. As shown in Figure 5, the estimated occupancy profile indicates that very few people come to work on weekends and holidays. It is recommended that the occupancy profile be recorded at 15-minute or 1-minute intervals for effective validation of the occupant detection algorithm. Using this method, the estimated occupancy profile can be imported into the simulation model to replace the default occupant densities and schedules on weekdays, weekend and holidays of each month.

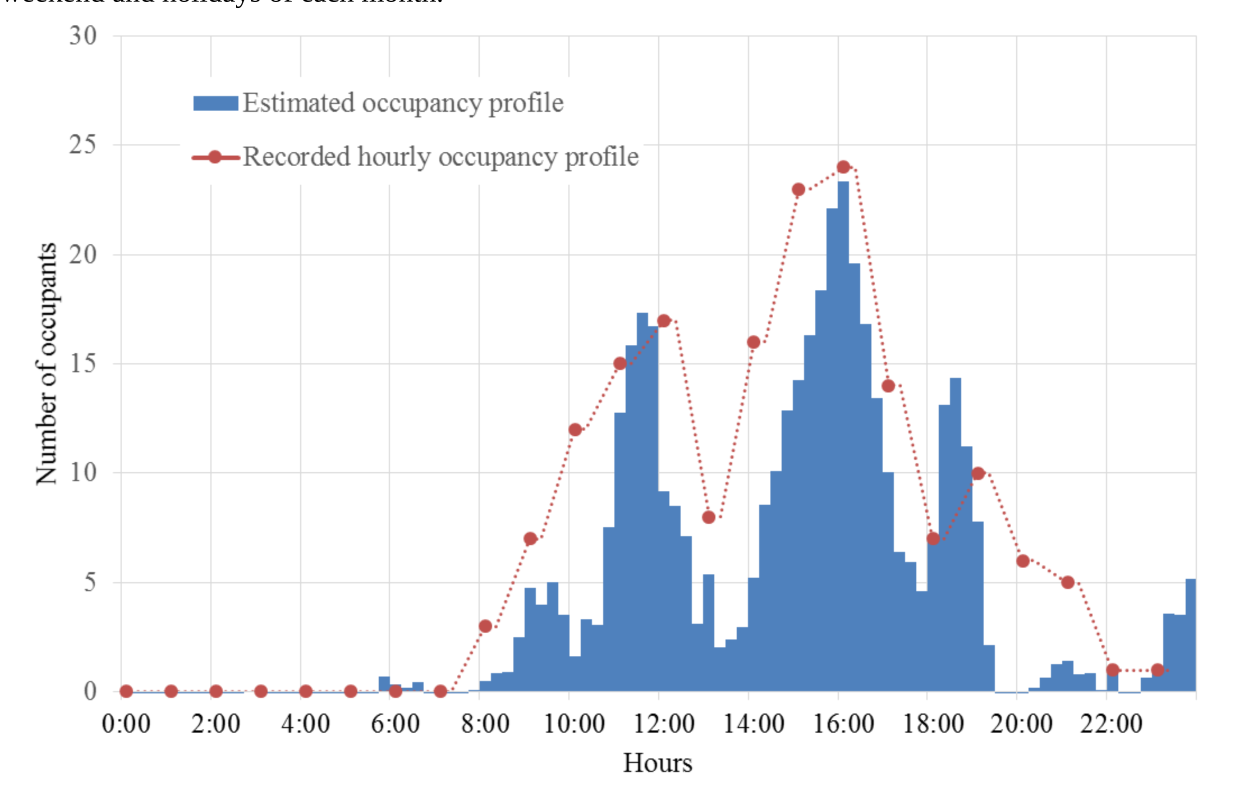

Figure 4: Estimated occupancy profile in an open office area on a test day

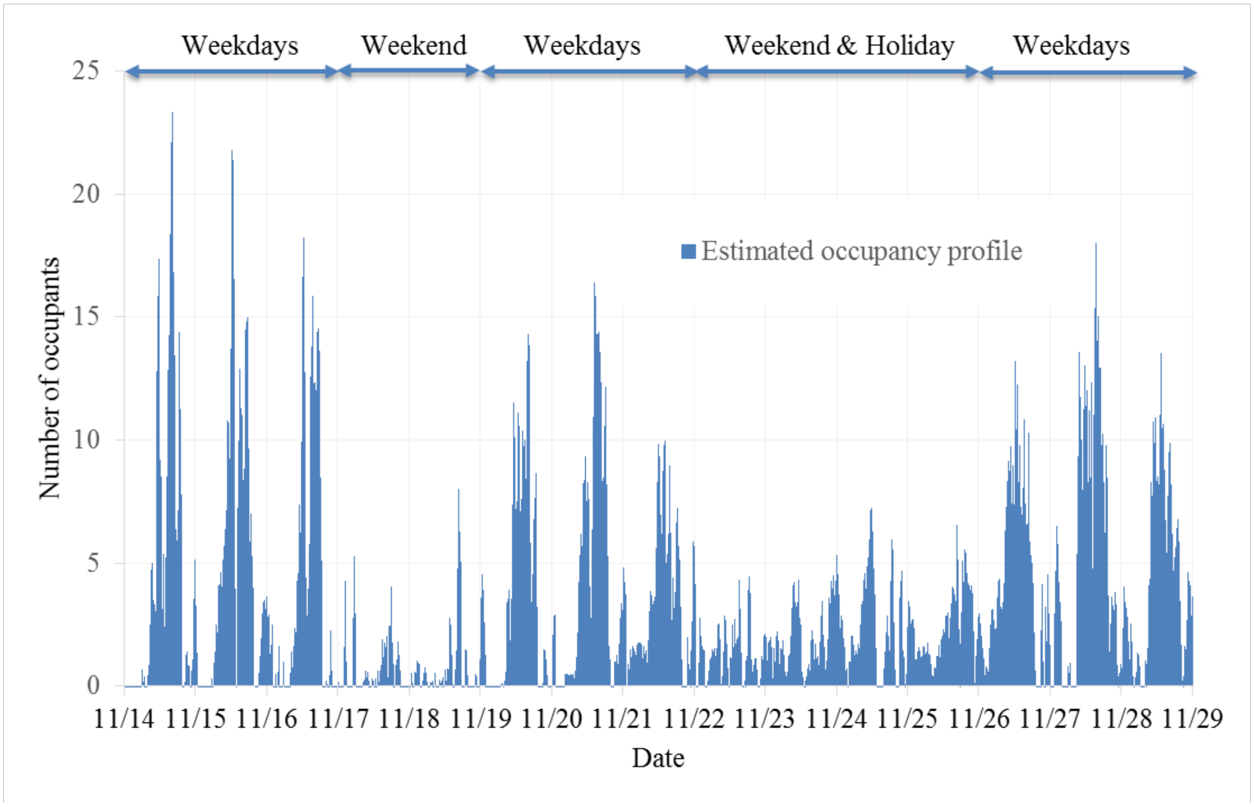

Figure 5: Estimated occupancy profile in an open office area over two weeks

3.1.2 Lighting and plug loads

The increasing implementation of sub-metering in buildings resolves the above problems with estimation. In this study, it was proposed that we combine the lighting sub-metering system and the field plug load audit to feed the actual lighting and plug load densities and schedules into the model. As shown in Figure 6 and Figure 7, the actual operational schedules of the lighting and plug loads on the fourth floor can be obtained from the monitoring system via sMAP and imported into the model either off line or in real time. Notice that the lighting system usually turns on at 7AM, and most students come to work in open offices starting at 10AM, as indicated by plug power usage. Most of the plug loads were still on during off hours.

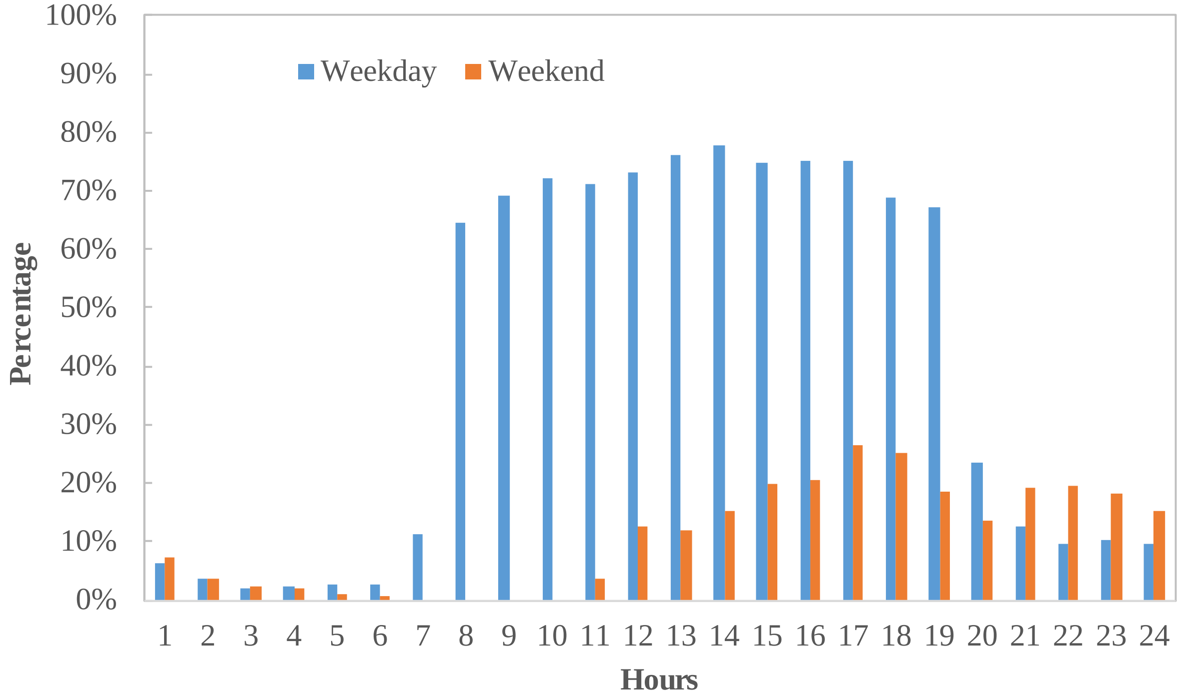

Figure 6: Calibrated 4th-floor lighting power schedules on weekdays and weekends

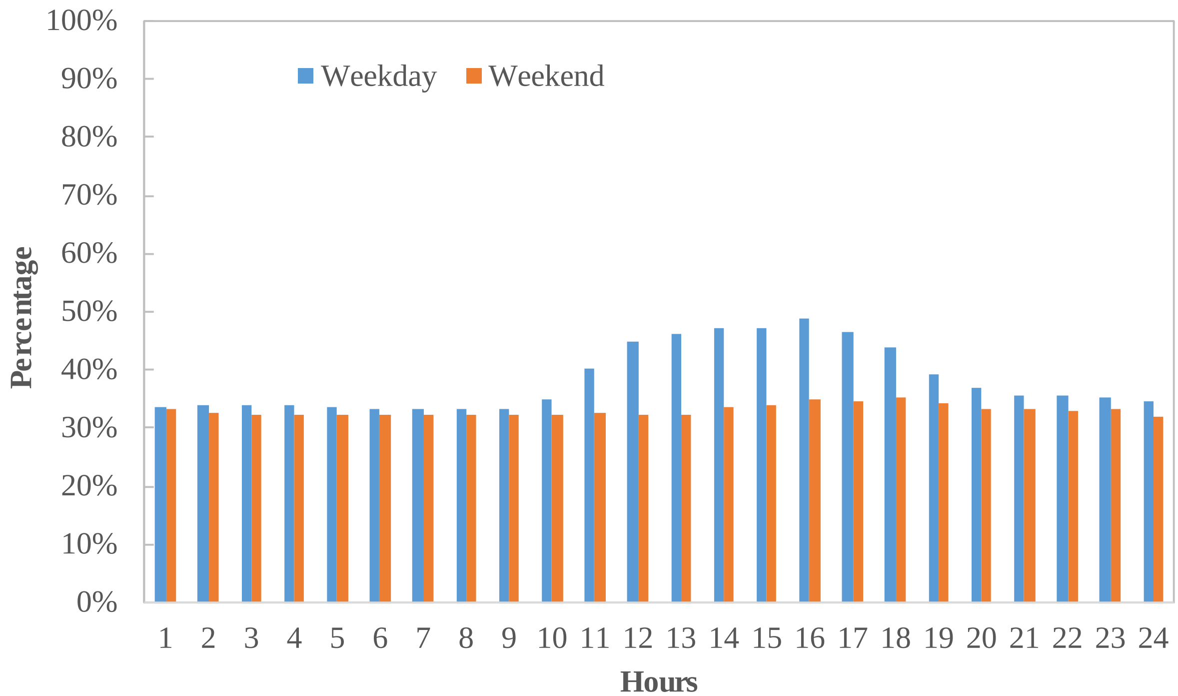

Figure 7: Calibrated 4th-floor plug power schedules on weekdays and weekends

Table 4 compares the initial estimated and calibrated plug loads for each floor. The initial plug load power density was estimated as 13 W per square meter (W/m^2) in the office area, and each floor's plug load was determined through a detailed plug load audit. Differences between the initial estimated and calibrated plug load power usage are about -55%~27.6%. For building spaces with different functionalities, it is very challenging to accurately estimate plug power use without sub-meters or detailed building audits. Even with a comprehensive building plug load audit, it is hard to understand the plug load schedules at the building or floor level.

Table 4: Comparisons of initial estimated and calibrated plug load on each floor

No. Floor	Initial estimated (kW)	Calibrated (kW)	Differences
1	32.4	25.4	27.6%
2	13.5	30.0	-55.0%
3	8.2	15.5	-47.1%
4	10.4	16.7	-37.7%
5	12.9	15.7	-17.6%
6	6.8	6.9	-2.0%
7	8.5	12.5	-32.1%

3.2 Air-side components

3.2.1 Variable air volume

Taking the advantage of the VAV-based zoning approach, the physical data points from sMAP were derived and fed into the model, including each control zone's thermostat temperature set point and minimum/maximum airflow rates under heating/cooling mode. All of these parameters are essential to capture the zone-by-zone thermal load and corresponding VAV performance. Figure 88 shows the significant difference between the original simulated airflow rate from ASHRAE 62.1-2007 and the design airflow rate. The design minimum ventilation rate is very close to the value required in California building code Title 24-2008. Most of the building's VAV terminals are oversized and thus have higher minimum airflow rates, which causes a discrepancy in the supply fan airflow rate under cold or cool weather conditions. This discrepancy between the standard and the design ventilation rate could lead to lower fan power predictions from the model when most VAV terminals are running in minimum mode. At the same time, this discrepancy means that nearly 30% of the difference between the measured and the standard minimum ventilation rates could be applied to reducing building HVAC demand.

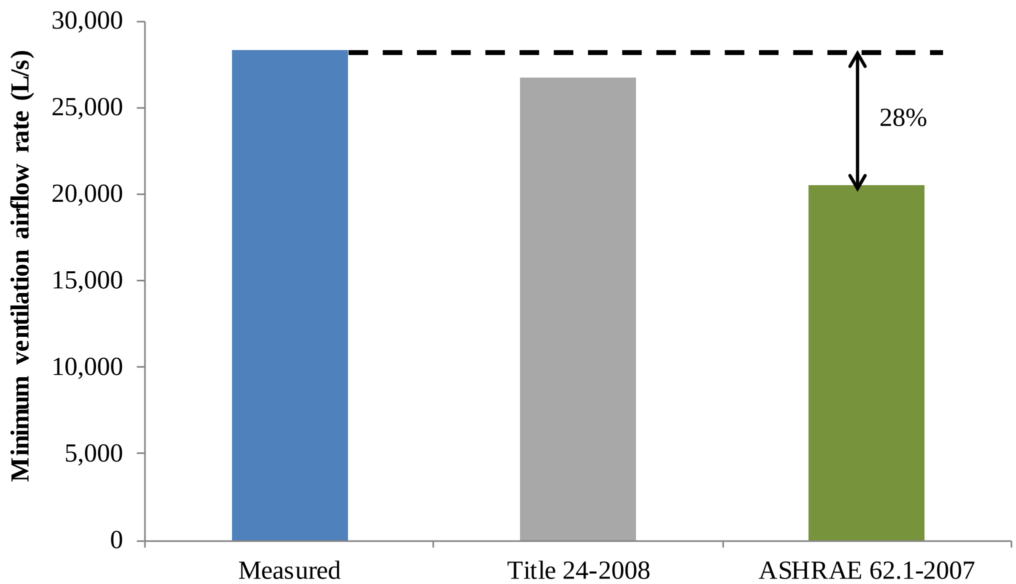

Figure 8: Comparisons of design, Title 24-2008, and ASHRAE 62.1-2007 minimum ventilation rates

3.2.2 Air-handling units

With regard to fan power calibration, the part-load curve can have a major impact on simulated fan power usage. The actual operational curve can be different from the manufacturer reference curve or laboratory data. Therefore, it is important to derive the operational curve from measured data. AHUs usually contain more than two parallel fans. It is not easy to simulate this type of fan configuration in some simulation tools. If the parallel fans are identical and running in a similar operational mode, an accurate part-load curve can be applied to create a virtual large fan that represents the parallel fans.

Using measured data on supply airflow rate and fan power percentage, we developed the actual fan operational curve of part-load performance shown in Figure 9. Because of the limited range of fan operation, two virtual points were put into the data set to stand for the operational conditions when the supply fan is running at 100% load. However, the data set is still missing large ranges of fan operational conditions that cannot be obtained from the building monitoring system. To validate the new operational curve, we derived another new set of data points from the monitoring system.

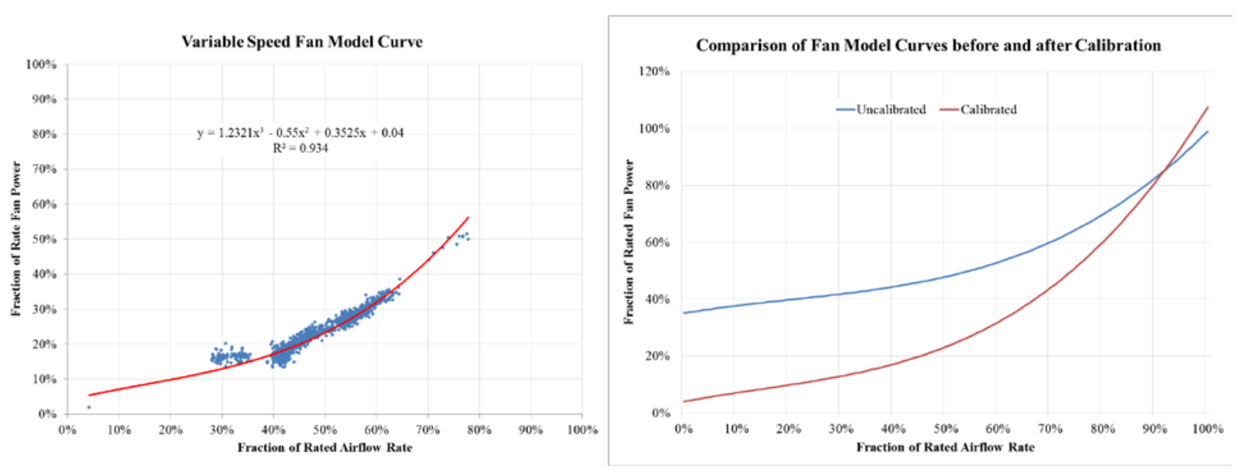

Figure 9: Comparison between reference and actual operational fan part-load curves

Figure 10 compares measured and predicted power load fraction. The validation results indicate that the new curve captures the fan performance well under different operational conditions.

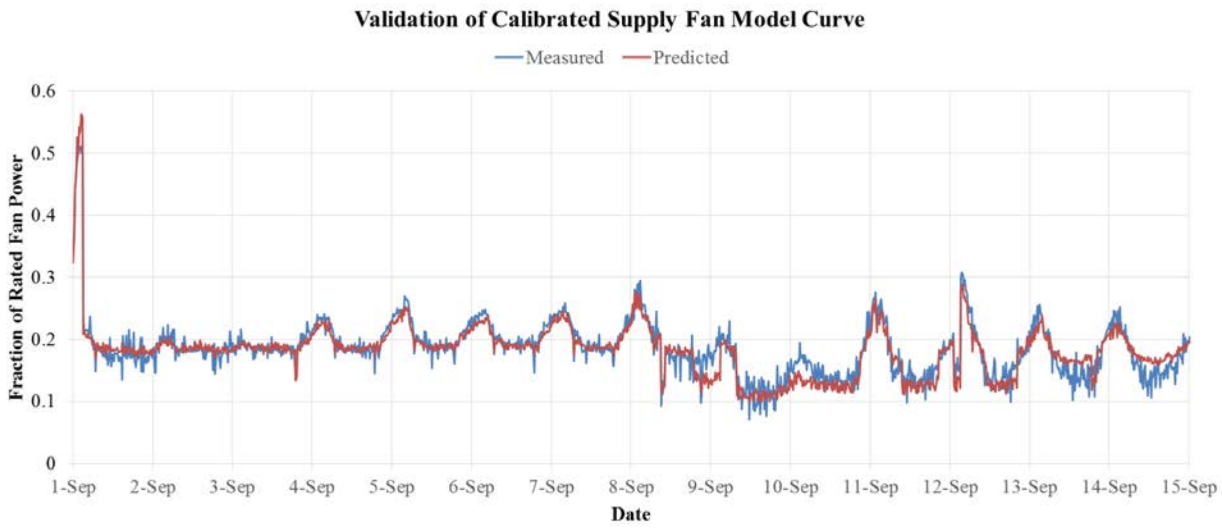

Figure 10: Validation of the new supply fan operational curve

3.3 Water-side components

Three curves affect the electrical chiller cooling capacity performance: function of temperature, electrical input to cooling output ratio function of temperature, and electrical input to cooling output ratio function of part-load ratio curve (EnergyPlus). Those curves are used to capture the difference between the actual operational conditions and the design conditions, including the temperature of water exiting the chiller, the temperature of water entering the condenser, and the part-load ratio. Therefore, it is crucial to calibrate these three curves using real-time measured data. As shown in Figure 11, all chiller operational curves are derived for a set of monitoring data points and validated by using a new set of data points. The cooling tower requires only one curve, which is similar to the supply fan operation curve. The variable-speed tower model is based on empirical curve fits of field measurements. Given the airflow rate and fan power percentage, the cooling tower fan power ratio curve can be easily calibrated as shown in Figure 13.

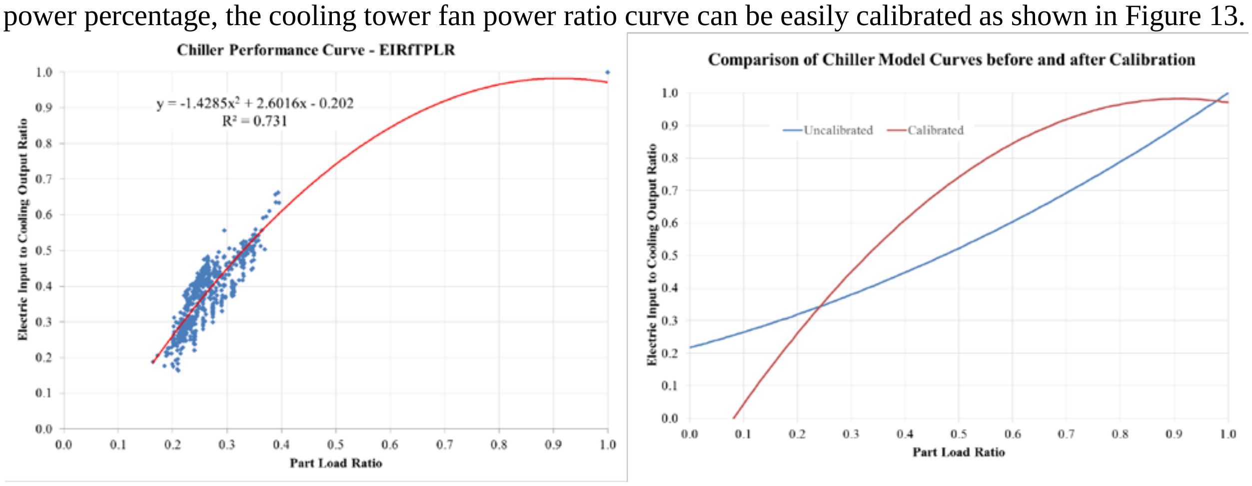

Figure 11: Electrical input to cooling output ratio function of part-load ratio curve

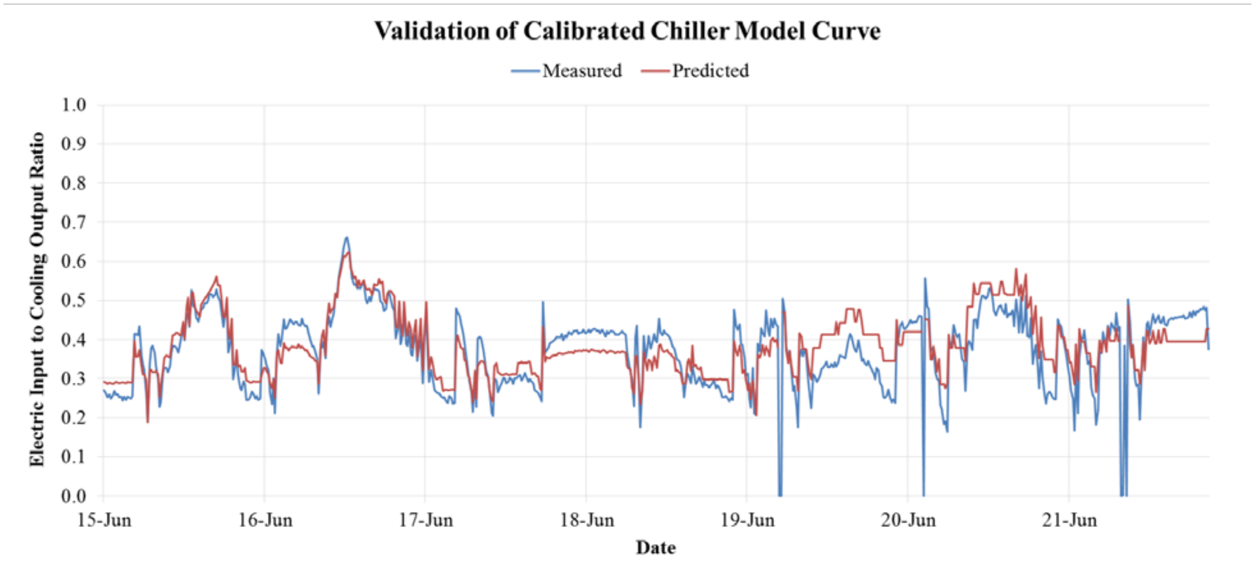

Figure 12: Validation of calibrated chiller model curve – Electric input to cooling output ratio

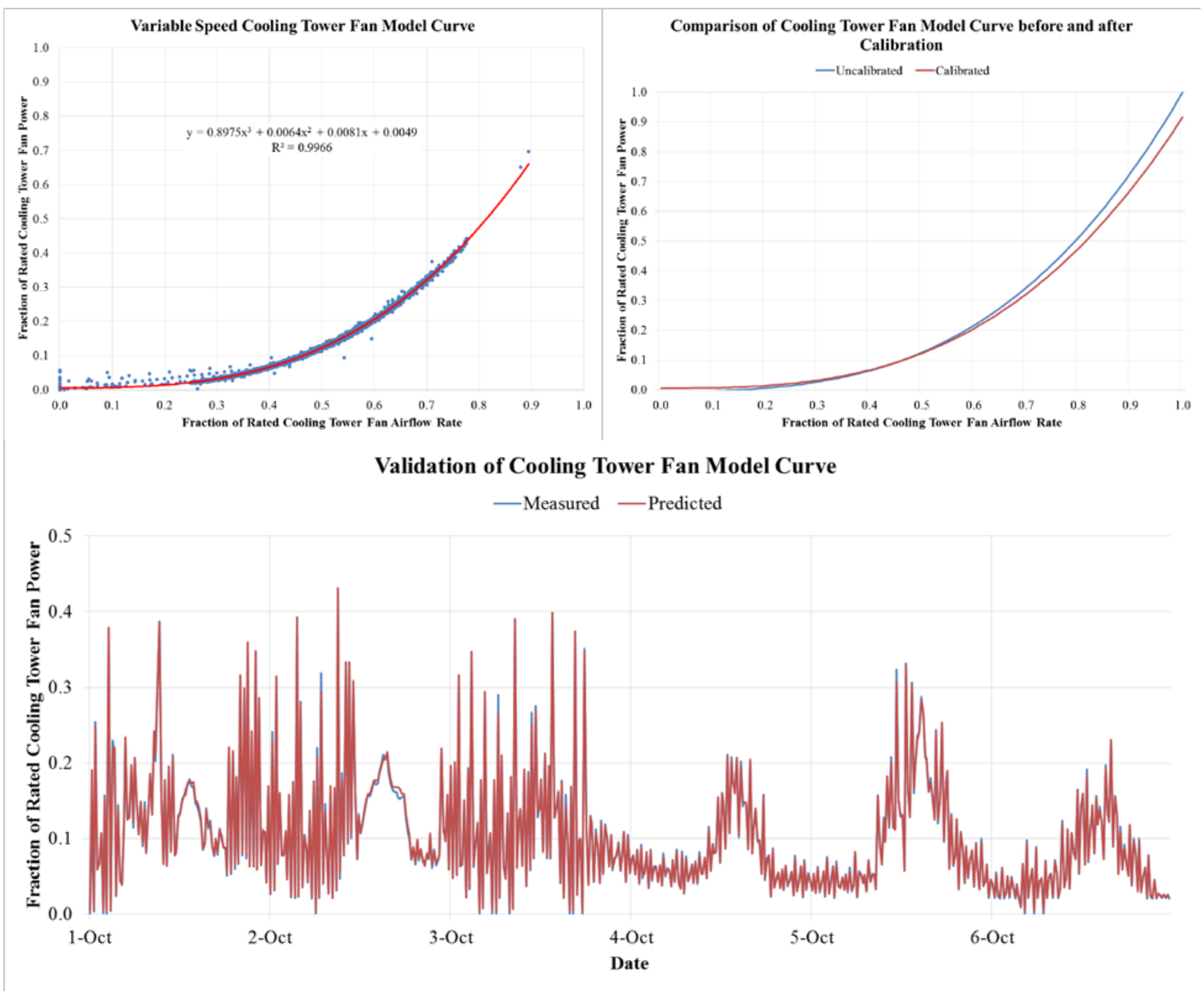

Figure 13: Cooling tower fan power ratio as function of airflow ratio

4 Results

The following subsections compare simulated and measured results for lighting, plug loads, AHUs, and cooling tower power usage in the case-study building. In addition, we show how the calibrated model was validated with simulations of DR control strategies that demonstrate its ability to predict dynamic building responses.

4.1 Lighting, plug, air-handling unit, and cooling plant power usage

Figure 14 shows the measured lighting and plug power consumption plotted against the simulated data for every 15 minutes during a week in July, 2011. NMBE and CV(RMSE) for this comparison are 7.5% and 12.5%, respectively, indicating that the model's predictions of plug power usage show good agreement with the measured data.

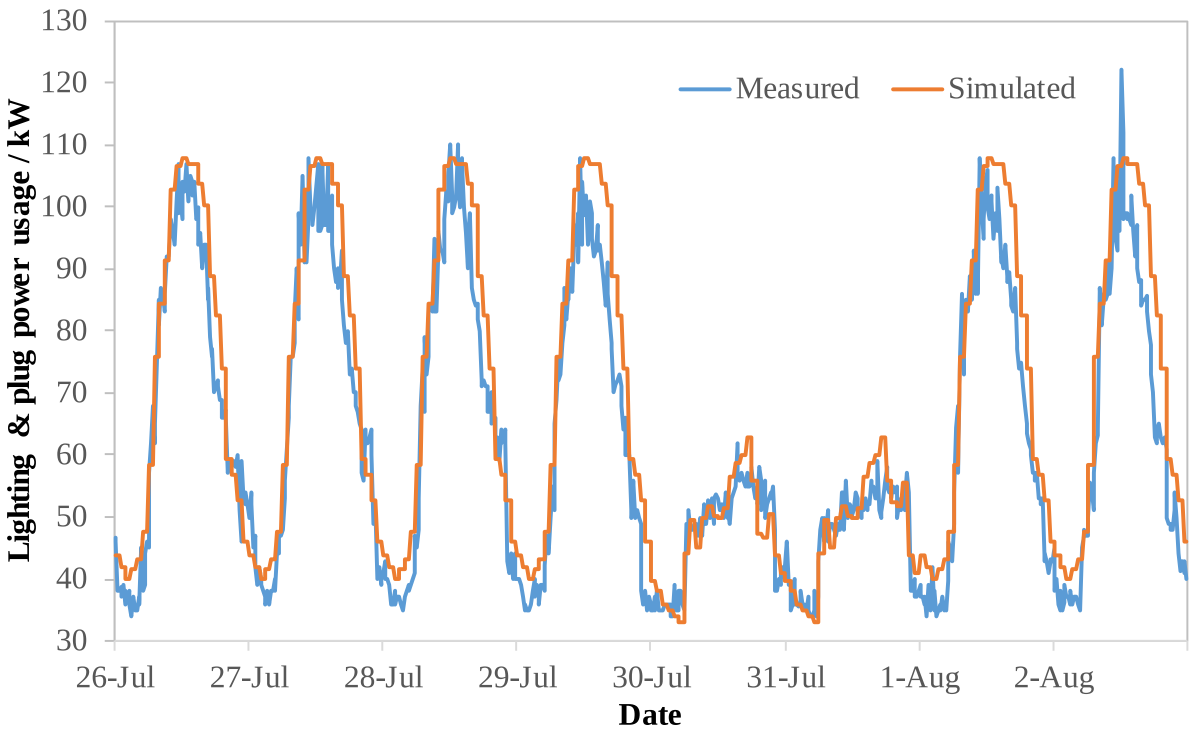

Figure 14: Comparison of measured and simulated lighting and plug load power usage during a week in summer 2011

The comparison between calibrated simulation and measured results yields a monthly MBE within 10%. Using a new data set to evaluate the model's predictions at the hourly level, we see that the hourly simulation results match the measured results with 20% for at least 20 of 24 hours each day. The calibration results meet the whole-building calibrated simulation performance requirement in ASHRAE Guideline 14.

Using the calibrated fan model curve described earlier along with calibrated space loads (occupant, lighting, and plug) substantially improves the accuracy of the simulated fan power in relation to measured data. Figure 15 shows how the calibrated supply fan power matches the measured data. The simulated fan power usage showed good agreement with the measured data during most operational hours. NMBE and CV(RMSE) for this comparison are -1.8% and 5.7%, respectively.

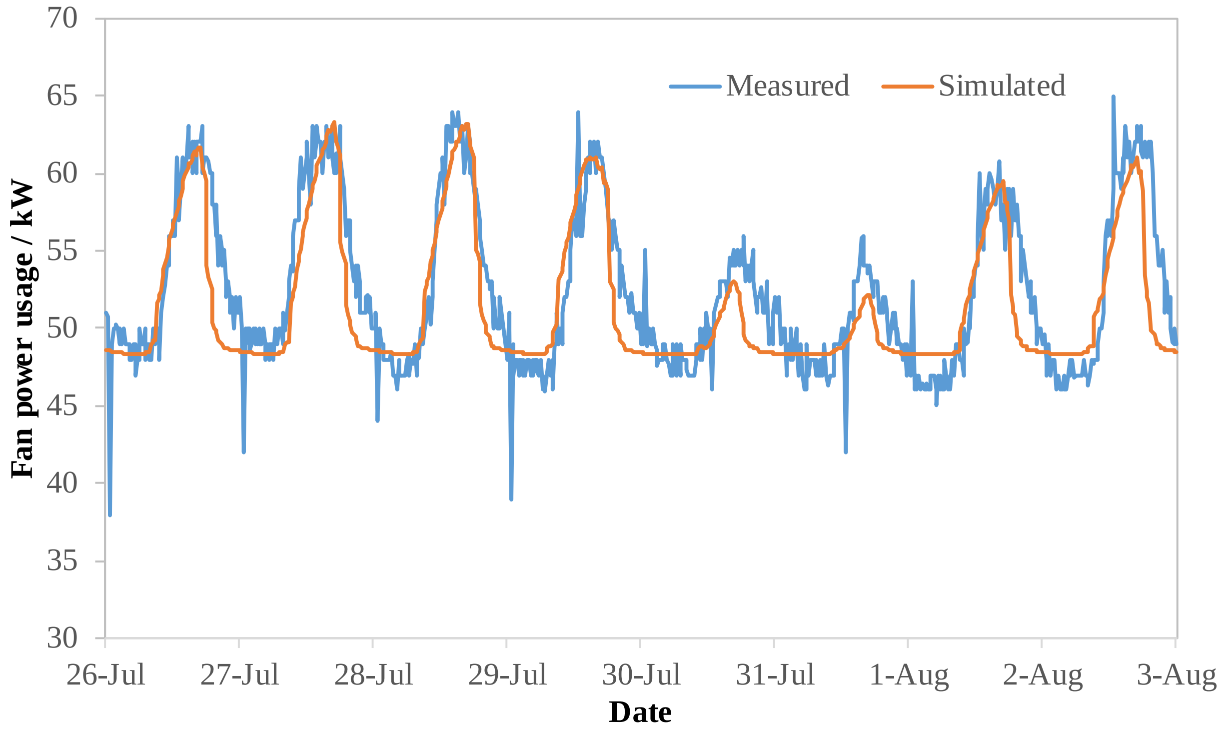

Figure 15: Comparison of sub-metered power usage of supply fans, return fans, and two exhaust fans

During the test period in summer 2011, the building's monitoring system showed that the centrifugal chiller was short-cycling at low load. As a result, the building ran the absorption chiller, so there were no available data points for the electrical chiller to compare to simulated results. Also, between September and November, the minimum ventilation airflow rate was reset at 70% of the original value for most VAV boxes. The calibrated model adjusted the minimum airflow parameter to match actual operation. Table 5 shows that the model error remains within the acceptable range with this adjustment.

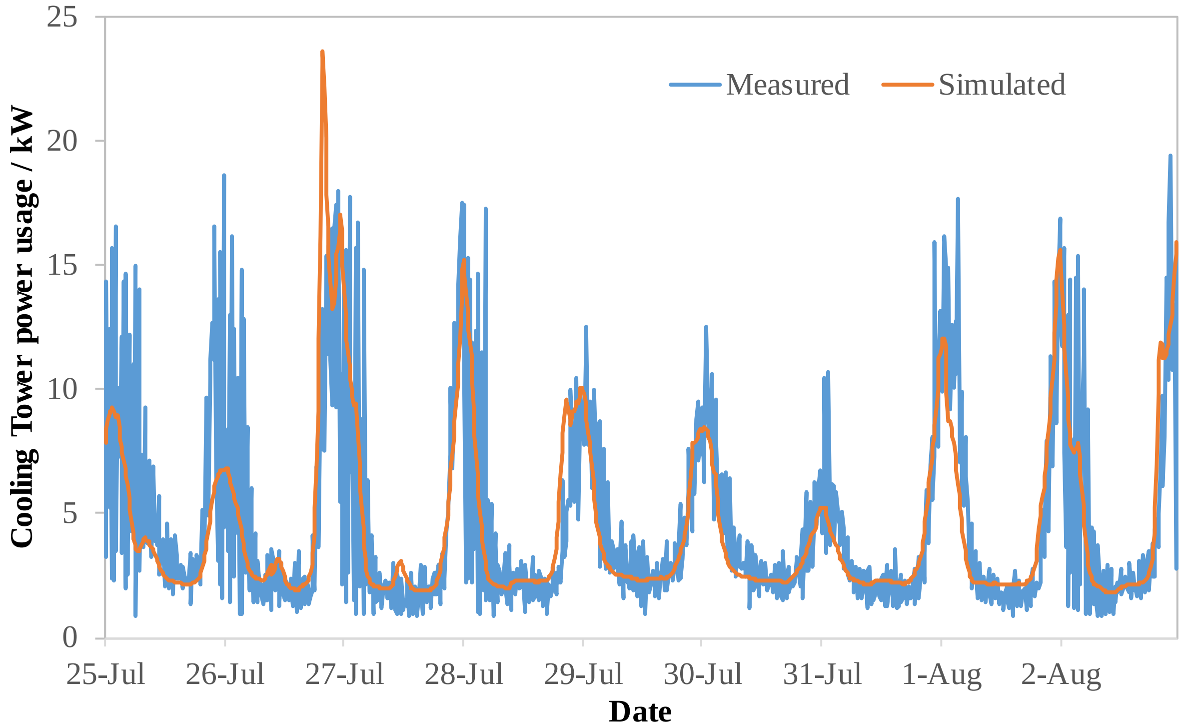

Figure 16: Comparison of cooling tower measured and simulated power usage during a test week

As summarized in Table 5, calibration significantly improved the EnergyPlus model's accuracy to 5.7% for the VAV fan system and 12.5% for the lighting and plug loads. In addition, the model's ability to forecast AHU performance during periods of reduced ventilation rate still satisfies the model calibration tolerance.

Table 5: Results of model calibration based on monitoring data

Electric Load	Test periods in 2011	NMBE	CV(RMSE)
HVAC – AHU (Original ventilation)	Jul 25th to Aug 3rd	-1.8%	5.7%
HVAC – AHU (70% of Minimum airflow)	Sep 24th to Oct 24th	7.7%	10.7%
Lighting & Plug load	Jul 25th to Aug 3rd	7.5%	12.5%
HVAC – Cooling Tower	Jul 25th to Aug 3rd	1.8%	40.9%

4.2 The Model's Prediction of Dynamic Response

The calibrated model results show good agreement with measured building data at the whole-building and sub-utility system component level during normal operating conditions. The model faces an additional challenge in predicting the effect of dynamic response control strategies on major system components, including supply and return fans serving the office portion of the building.

A DR event was called at the building on August 22, 2011. A set of DR strategies was tested between 2 pm and 7:30 pm. First, at 2 pm, supply air temperature was increased 2°F, from 56°F to 58°F. An hour later, the supply air temperature was increased by an additional 2°F. An hour later, all VAV boxes were controlled to provide ASHRAE default ventilation rates, which were 30% less than the building's normal ventilation rates. At 4:40pm, zone temperature set points were increased from 70°F to 74°F. At 6:30pm, the reheat coil was disabled in the building. Finally at 7:30pm, all systems reverted slowly, over an hour, back to normal operation. Figure 17 compares the simulated and measured supply and return fan power usage during the DR test event. Notice that the actual system response time for temperature adjustments (e.g., raising supply air temperature, raising thermostat set point) was longer than the response time for reducing the VAV minimum airflow rate. The model did not capture the response time for activating the control signal in the BMS. The calibrated model gives a good prediction of dynamic controls; the NMBE and CV(RMSE) are -3.6% and 7.1%, respectively.

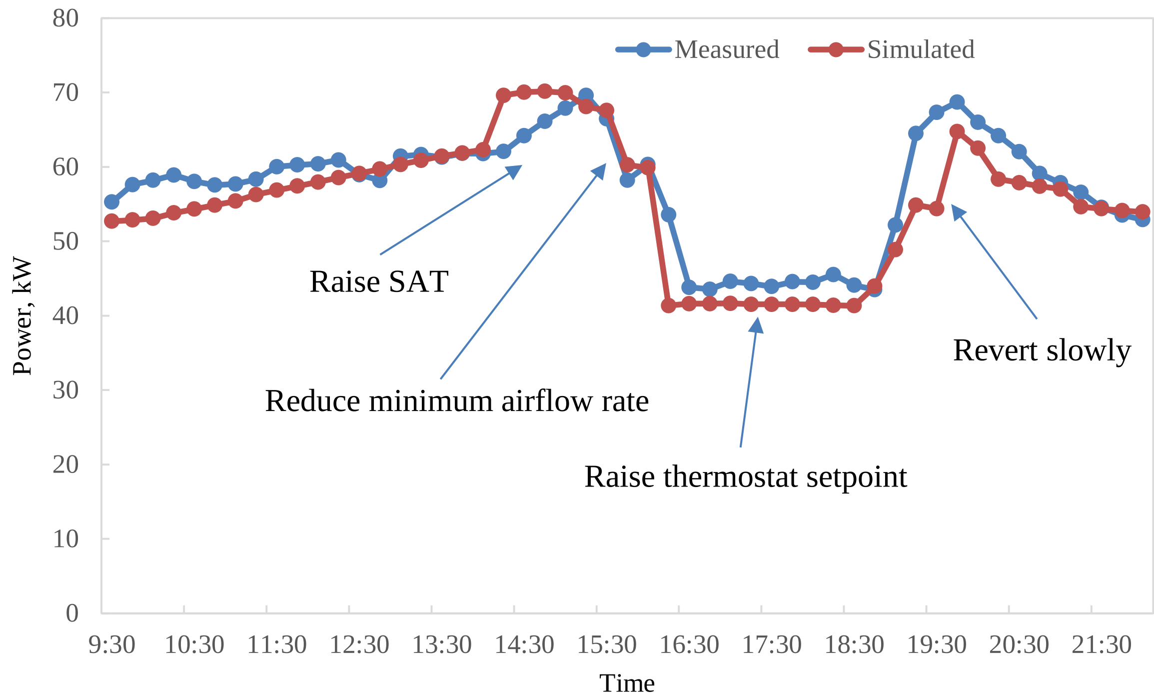

Figure 17: Comparison of measured and simulated supply and return fan power during a DR test event

On August 2, 2012, the team conducted another integrated test of various control strategies for demand reduction during the peak hours of 2pm to 6pm. From 11:30am to 2:30pm, the building was pre-cooled by reducing the global temperature set point to 70°F from 72°F. As noted earlier, the effect of utilizing building thermal mass for pre-cooling has been demonstrated in field test studies (Xu et al., 2007; Yin et al., 2010). From 2:30pm to 6pm, the global temperature set point was reset to 76°F, and the minimum ventilation rate for all VAVs except those in electrical rooms was reduced by 70% of the original value. At the same time, the supply air temperature was raised 2°F from 58°F to 60°F, and the lighting and receptacle loads were reduced by about 40% throughout the building. The exactly same control strategies were implemented in the model. Table 6 shows the comparison between measured and modeled results. We can see that the model's prediction of increasing power for pre-cooling the building is underestimated in comparison to the measured data. For demand reduction, the predicted results are very close to the measured data because the AHUs dropped to their lowest ventilation rate during the on-peak test period. When the rate is that low, there is very limited room for model uncertainties to affect the prediction of AHU power savings.

Table 6: Comparison between measured and simulated AHU performance during a DR test event (Peak outside air temperature: 70°F)

Test periods	Pre-cooling hours			DR event hours		
Demand savings (kW)	Min	Max	Ave	Min	Max	Ave
Measured	-39.9	-20.1	-32.7	20.0	31.3	26.6

Simulated	-23.9	-19.1	-21.4	25.0	29.7	27.0

5 Application of the calibrated model to demand response

To achieve the goal of 30% peak demand reduction in the building, various DR strategies were proposed that addressed HVAC, lighting, and plug loads. After implementation of best practices for lighting and plug loads, significant demand reduction was still needed; the additional reduction had to come from the HVAC system. A common strategy for reducing HVAC system power is to pre-cool the building prior to a DR event and adjust global temperature set points during DR event hours. However, the HVAC system's capacity for demand reduction is limited, so a more aggressive control strategy was required. Thermostat set-point adjustment combined with a reduction in minimum airflow is an aggressive DR control strategy that takes full advantage of VAV system. Both field and laboratory studies show that reduction of minimum VAV airflow rate can significantly reduce energy use without increasing occupant dissatisfaction (Arens et al., 2012).

To evaluate the effect of different control strategy combinations, we demonstrated the use of the calibrated model. For this case study, we conducted a comprehensive matrix of simulations on a hot day with peak outside air temperature of 90°F. Multiple levels of DR, from low to high, were defined. The ASHRAE thermal comfort standard permits only 6°F of temperature drift and ramp during a period of 4 hours (ASHRAE Standard 55, 2010). Relatively comfortable building conditions can be maintained within a range of space temperatures from 70°F to 78°F (Xu et al., 2008). The thermostat set point adjustment was simulated at various levels: 2°F, 3°F, 4°F, 5°F, and 6°F higher than the original set point. The minimum ventilation rate for VAVs was simulated at 30%, 40%, 50%, 60%, and 70% of the original value. The simulation results were put into a simple look-up table to enable selection of the optimal control strategy that would meet the peak-demand reduction goal under specific weather conditions.

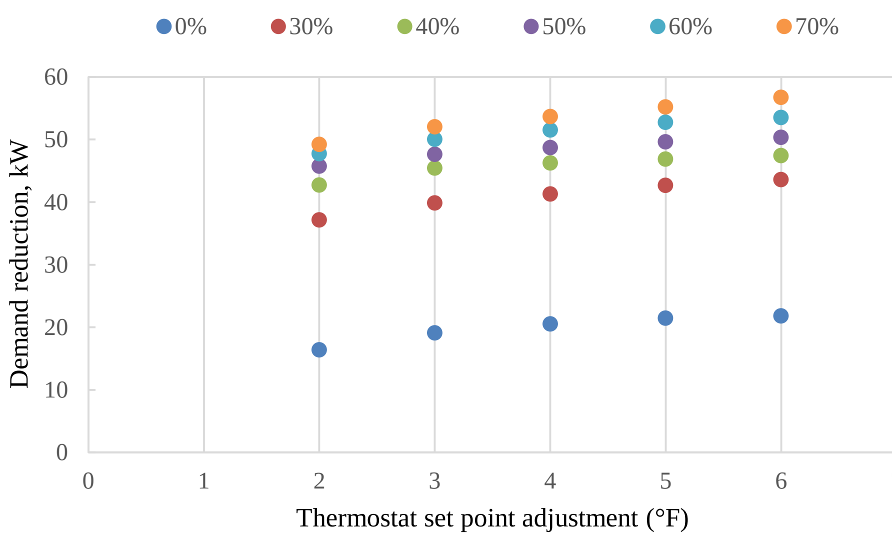

Figure 18: Comparison of peak demand reduction from HVAC system for all control scenarios

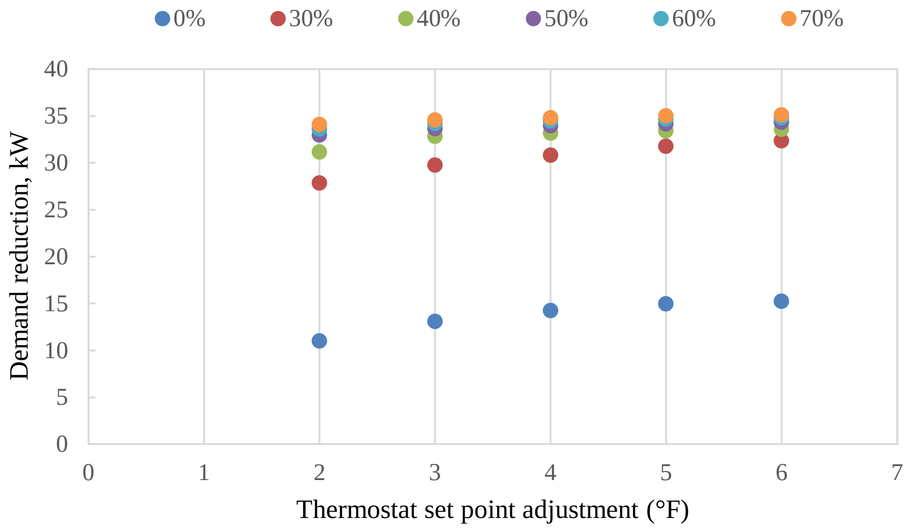

Figure 19: Comparison of peak demand reduction from AHUs for all control scenarios

Figure 18 and Figure 19 compare the peak demand reduction from the HVAC system and the AHUs. As we can see in Figure 19, there is a bottom line of demand reduction from the AHUs for the control strategy of minimum ventilation rate adjustment. Reductions beyond 40% of the original minimum ventilation rate show very little impact on AHU power savings for thermostat set-point adjustments. The reason is that most VAVs would run above the minimum ventilation rate on such as hot day. A building with an oversized ventilation rate can save more power from the AHUs by combining minimum ventilation rate adjustments with thermostat adjustments. As for the whole HVAC system, the power usage of the chiller, cooling tower, and pump decrease with increasing thermostat set points. The calibrated model can provide the facility manager with a reliable prediction on which to base a smart control strategy to achieve the peak-demand reduction goal.

6 Discussion

This study demonstrates a bottom-up, component-based method of calibrating a building performance simulation model. For this process, the model description needs to be well balanced, taking into account available building information, the model's use and computation speed, and other relevant factors. For modeling existing buildings, it is very important to make use of sensor and meter data to calibrate the model. For example, thermal zoning in this study was developed based on the case-study building's actual VAV control areas. Each VAV terminal, key parameters, e.g., minimum/maximum airflow rate, can be input to the model. The principle underlying this approach is to put all pieces of evidence or data from the building into the model. However, including every data point from a building can make the process of model calibration very time-consuming. The energy balance in a building energy simulation, in which three major parts of a model (building, system, and plant) can be simulated either simultaneously, suggest that an effective way to calibrate a model is to break down systems into their components and to validate the model inputs from the building to the system to the plant. Identifying the uncertainties in the key input parameters can also help reduce complexity and the effort to validate a model.

Skepticism is sometimes expressed about the predictions of even a well-calibrated model because a model is static whereas a building's operational behaviors are dynamic. For a model to accurately reflect a building's changing operations, especially for advanced-use real-time model simulations, the model must be connected to the BMS so that monitoring data can be imported automatically into the model in real time. In these cases, an automatic process for model calibration is essential to incorporate actual operational data. A direct connection between the model and the BMS with automated model calibration reduces the time and effort related to developing model inputs and verifying them against actual building performance. The auto-calibration approach will be very effective as sensors and meters are increasingly deployed in BMSs.

Another option is to construct a hybrid: a combination of the data-driven model with a physical model in a diagram. For example, a building cooling load model could be developed using measured data from sensors and meters installed in the HVAC system and plant. This data-driven model of cooling load could be connected to other physical model components in a loop. However, this type of model would not be useful for analysis of some building components, such as the building envelope and daylighting.

As indicated in the study, the approach of model development and calibration requires many meters and sensors, which could be very challenging to scale up for hundreds of buildings. It would be very efficient to focus on key parameters that have uncertainties such as space loads (occupancy, lighting and plug), HVAC system components' specifications and actual operational conditions. Without meters and sensors installed in the building, the alternative method is to conduct a deep building audit and use the technical approach of load disaggregation from the whole building power.

To evaluate the performance of our calibrated model in predicting building behavior during DR, we assessed the model's accuracy in rendering the effect of various control strategies on peak-demand reduction. For the application of model for DR, the calibration of each VAV terminal should be paid more attention as the adjustment of thermostat setpoint gives direct impact on the fan performance. In the case-study building, which is over-ventilated, adjusting the thermostat setpoints did not take advantage of the full potential power savings from the HVAC system. An integrated control strategy of thermostat set point adjustment and minimum ventilation rate resets enabled multiple VAVs to run in a broad range, which increased the peak-demand savings. Overall, given a goal of peak-demand reduction on a certain day, the model can be used to run all kinds of control scenarios to provide the facility manager with reliable predictions that can be used as a basis for day-ahead or day-of DR operations.

7 Summary and Conclusions

This paper describes a case study of developing a building performance model for an existing campus building; calibrating the model using a bottom-up, component-based method; and applying the model to predict DR behavior in the case-study building. A wide variety of sensors in the building were linked to the model's inputs, allowing for automated calibration of the model. This is a fast efficient way to ensure accurate DR modeling. One of the key factors needed to calibrate the model was information on occupant behaviors. This information was validated using the relationship between indoor and outdoor CO_2 concentrations. After the calibration of other building components – lighting, plug, HVAC system, and plant loads – we conducted a field test of DR control strategies to evaluate the model's ability to predict dynamic building responses. The calibrated model yielded a very good prediction of AHU performance in a DR test mode; the model errors NMBE and CV(RMSE) were -3.6% and 7.1%, respectively. Another key finding of this study is that thermostat setpoint adjustment should be combined with a reduction in minimum airflow to achieve the best DR performance, especially in over-ventilated buildings.

In the future, automated model development and calibration will be widely used as Building Information Modeling and low-cost sensors and meters in buildings are increasingly deployed. As more and more data are available from buildings, each component of a physical model can be represented as the input to a data-driven model. Such a hybrid model can accurately predict a building's dynamic response during DR, event and can also optimize building operation under normal conditions.

8 Acknowledgments

This work described in this paper was coordinated by the University of California at Berkeley, Siemens Corporation Research, and the Lawrence Berkeley National Laboratory (LBNL) Demand Response Research Center and was funded by the U.S. Department of Energy, under DOE contract DE-AC02-05CH11231, Award Number DE-EE0003847. The authors are grateful for the extensive support from the Auto-DR program managed by the Demand Response Research Center at LBNL. Special thanks to Prof. David Culler, Prof. David Auslander, and Therese Peffer for providing their insight and support, and to Jianmin Zhu from Siemens Corporate Research. Thanks also to University of California building manager Domenico Caramagno for providing technical support.

9 References

ASHRAE, ANSI/ASHRAE 62.1-2010 Ventilation for Acceptable Indoor Air Quality. Atlanta, GA, American Society of Heating, Refrigeration and Air Conditioning Engineers, 2002

ASHRAE, ASHRAE guideline 14 for measurement of energy and demand savings. Atlanta, GA, American Society of Heating, Refrigeration and Air Conditioning Engineers, 2002

Arens, E., H. Zhang, T. Hoyt, S. Kaam, J. Goins and F. Barman, Thermal and air quality acceptability in buildings that reduce energy by reducing minimum airflow from overhead diffusers, ASHRAE 1515RP Final Report, 2012, CBE, UC Berkeley

Kim, J., R. Yin and S. Killiccote, Automated Price and Demand Response Demonstration for Large Customers in New York City using OpenADR, Lawrence Berkeley National Lab., Berkeley, CA, LBNL-6470E, 2013

Lam, K,, M. Hoynck, B. Dong, et al., Occupancy detection through an extensive environmental sensor network in an open-plan office building, in the 7th international conference of IBPSA, Glasgow, Scotland. July 27-30, 2009

Motegi, N., M.A. Piette, D. S. Watson, S. Kiliccote, P. Xu, Introduction to commercial building control strategies and technologies for demand response, Lawrence Berkeley National Lab., Berkeley, CA, LBNL-59975, 2007

Norford, L.K., R. H. Socolow, E. S. Hsieh, and G. V. Spadaro, 1994. Two-to-one discrepancy between measured and predicted performance of a 'low-energy' office building: insights from a reconciliation based on the DOE-2 model, Energy and Buildings 21 (1994), pp. 121-131.

New, J., J. Sanyal, M. Bhandari and S. Shrestha, Autotune E+ Building Energy Models, in Proceedings of SimBuild Conference of IBPSA-USA, Wisconsin, WI, 2012

Keeney, K., and J. E. Braun, Application of building precooling to reduce peak cooling requirements, ASHRAE Transactions 103 (1997), pp. 463-469.

O'Neill, Z., B. Eisenhower, Leveraging the analysis of parametric uncertainty for building energy model calibration, Building Simulation, no.6, pp.365-377, 2013

Pan, Y., R. Yin, Z. Huang, Energy modeling of two office buildings with data center for green building design, Energy and Buildings, vol. 40, no. 7, pp. 1145-1152, 2008

Reddy, T.A., M. Itzhak, and C. Panjapornpon, 2007. Calibrating detailed building energy simulation programs with measured data - Part I: general methodology, HVAC&R Research Journal 13 (2007).

Reddy, T.A., M. Itzhak, and C. Panjapornpon, 2007. Calibrating detailed building energy simulation programs with measured data - Part II: application to three case study office buildings, HVAC&R Research Journal 13 (2007).

Raftery, P.,, M. Keane, and J. O'Donnell, Calibrating whole building energy models: An evidence-based methodology, Energy and Buildings, vol. 43, no. 9, pp. 2356–2364, Sep. 2011.

Raftery, P., M. Keane, and A. Costa, Calibrating whole building energy models: Detailed case study using hourly measured data, *Energy and Buildings*, vol. 43, no. 12, pp. 3666–3679, Dec. 2011

Rabl, A., and L. K. Norford, Peak load reduction by preconditioning buildings at night, International Journal of Energy Research 15 (1991), pp. 781-798.

sMAP, the Simple Measurement and Actuation Profile. http://new.openbms.org/

Title 24, 2008 Building Energy Efficiency Standards for Residential and Non Residential Buildings, California Energy Commission, 2008.

Turner, C., M. Frankel, Energy Performance of LEED for New Construction Buildings, New Building Institute, Prepared for U.S. Green Building Council

U.S. Department of Energy, EnergyPlus 8.1, http://apps1.eere.energy.gov/buildings/energyplus/

Wang, L., S. Greenberg, J. Fiegel, A. Rubalcava, S. Earni, X. Pang, R. Yin, S. Woodworth, and J. Hernandez-Maldonado, Monitoring-based HVAC commissioning of an existing office building for energy efficiency, Applied Energy, vol. 102, no. 0, pp. 1382–1390, Feb. 2013.

Wang, S., J. Burnett, H. Chong, Experimental validation of CO2-based occupancy detection for demand-controlled ventilation, Indoor Built Environment, no.8, pp.377-391, 1999

Xu, P., P. Haves, J. E. Braun, and L. t. Hope, Peak demand reduction from pre-cooling with zone temperature reset in an office building, in Proceedings of 2004 ACEEE Summer Study of Energy Efficiency in Buildings, Pacific Grove, CA, 2004.

Xu, P., P. Haves, Case study of demand shifting with thermal mass in two large commercial buildings, ASHARE Transactions 112 (2005), pp. 875-888.

Xu., P, R. Yin, C. Brown, and D.E. Kim, Demand Shifting With Thermal Mass in Large Commercial Buildings in a California Hot Climate Zone, Lawrence Berkeley National Lab., Berkeley, CA, LBNL-3898E, 2009

Yin, R., P. Xu, M. A. Piette, and S. Kiliccote, Study on Auto-DR and pre-cooling of commercial buildings with thermal mass in California, Energy and Buildings, vol. 42, no. 7, pp. 967–975, Jul. 2010.

Yin, R., S. Kiliccote, M. A. Piette, and K. Parrish, Scenario Analysis of Peak Demand Savings for Commercial Buildings with Thermal Mass in California, 2010 ACEEE Summer Study on Energy Efficiency in Buildings, Pacific Grove, CA, August 15-20, 2010

Yoon, J., E. J. Lee, and D. F. Claridge, 2003. Calibration procedure for energy performance simulation of a commercial building, Journal of Solar Energy Engineering 125 (2003), pp. 251-257.

Zhu, J., L. Shen, R. Yin and Y. Lu, A two-stage simulation-based on-line optimization scheme for HVAC demand response, in the 5th National conference of IBPSA-USA, Madison, Wisconsin. August 1-3, 2012